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Double auction mechanisms for peer-to-peer energy trading: A comparative analysis

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***Abstract*—Peer-to-Peer (P2P) energy trading, one of the new paradigms driven by decentralization, decarbonization, and digitalization of the smart grid, has become a widespread technique in recent years. Additionally, the rise of the double auction for P2P energy trading suggests better trading algorithms with unprecedented economic and technical benefits. This work evaluates various discrete double auction mechanisms, i.e., Average, VCG, Trade reduction, and McAfee's for multiple microgrids. By doing this, the trading algorithm provides players more flexibility to decide from the types of double auctions available. We further study properties such as individual rationality, balanced budget, truthfulness, and economic efficiency associated with energy trading. For practical applicability, we simulate the functionality of the trading algorithms using IEEE LV feeder data. In the end, this work demonstrates a variation in energy trading and social welfare due to the time of usage tariff and change in bidding range.**

Keywords— Peer-to-peer, energy trading, double auction, economic properties, multiple microgrids, bidding range, trading algorithms.

I. Introduction

According to the Electric Power Research Institute (EPRI), full development of smart grid technologies in the distribution network can save between $1.3 and $2 trillion [1]. In recent years, the energy sector has experienced a worldwide proliferation of integrated renewable sources, increased demand for energy efficiency and improved technologies in smart grid operation. As the number of technologies rapidly grows, distribution companies must determine how to assimilate these assets while delivering reliable, secure and affordable electricity. One of the most popular approaches to assimilating these assets is establishing electricity markets and allowing open competition between providers, for example, by establishing peer-to-peer(P2P) energy trading markets. Several definitions of P2P energy trading are used in the literature[2]–[6]. P2P energy trading is described as a platform to match prosumers and consumers using mutually accepted regulations and provide information about trading among players [2]. Using P2P, peers are expected to generate revenue by acting as major energy providers and, therefore, reduce their dependence on distribution companies and fossil-based power plants [3]. Some of the advantages of P2P energy trading outlined in earlier studies are as follows: (a) Consumers can generate economic benefits from P2P energy trading by purchasing energy from prosumers at a lower price as compared to the tariff offered by the distribution company [4]. (b) Reducing energy costs and higher energy accessibility contribute to sustainable cities using P2P energy trading [5]. (c) P2P energy markets can also be used to provide specific-purpose grid functions such as voltage management and demand response [6].

Various game theoretical models are available to generate trading algorithms based on auction mechanisms [12], cooperative games [7], [8], and non-cooperative games [9]. The most popular game theory is the auction mechanism that allows consumers and prosumers to trade energy according to their desired price. The use of double auction mechanism for P2P energy trading has resulted in better trading algorithms with unprecedented economic and technical benefits [10]. The proposed study seeks to pursue the following objectives:

- The first objective of this study is to conduct a comparative analysis of various double-sided auctions (DSA): Average, Vickrey-Clarke-Groves, Trade Reduction, and McAfee mechanisms.
- The second objective of this work is to identify the significance of economic properties such as individual rationality, balanced budget, truthfulness, and economic efficiency when using double auction mechanisms in P2P energy trading.
- The study also examines the effect of bidding range and time-of-usage (ToU) tariff on DSA mechanisms in multiple microgrids.

Unfortunately, these economic properties of the DSA market have been consistently ignored in the literature for devolving trading algorithms in P2P energy trading. Research has tended to focus on double auction for devolving trading algorithms in P2P energy trading without exploring economic properties. Additionally, while the performance of individual mechanisms has been demonstrated previously, the comparative performance of the different mechanisms has not been compared for P2P energy trading.

II. Double-Sided Auction

In double-sided auction (DSA) mechanisms, multiple consumers and prosumers have the opportunity to trade energy simultaneously at a single time interval. The DSA market asks consumers to submit the bid price (BP), the maximum price they are willing to pay, and prosumers to submit a selling price (SP), the minimum price they want to receive for selling surplus energy [11]. The auctioneer, or market institution, collects the data from both players and sorts the price, and the trading price that clears the market is calculated [12]. The simplest example of a DSA market is a bilateral trade scenario [13], where consumers and prosumers submit their individual prices. In a more advanced/complex DSA market, a single consumer can buy energy from multiple prosumers to complete its demand. Similarly, a single prosumer can sell the surplus energy to multiple consumers in the network. In this scenario, if $\boldsymbol{BP \geq SP}$ the trading price is calculated by the market institution, whereas if $\boldsymbol{BP < SP}$ no trade occurs. The consumer utility is calculated as the difference between the true value to the consumer and the trading price, and the utility of the prosumer is calculated as the difference between the trading price and the true value to the prosumer. In this type of market, Equilibrium price ($\boldsymbol{P_{Eq}}$) is calculated using Natural Ordering and Breakeven Index [14]. The difference in the buying price and the selling price is expressed as the sensitivity of the price and is bounded by the maximum price set, known as the ceiling level and the minimum price, known as the floor level. The floor and ceiling prices are computed according to the minimum feed-in tariff that a utility has to pay to an independent prosumer and the maximum tariff cost that a distribution company takes from the consumer, respectively. According to the load curve, these levels can remain constant for the entire day or shift. Such differences between the floor and ceiling are varied in this work to analyse the impact on DSA mechanisms. This kind of approach allows for price discovery within the range and is underway in many parts of the United States [15]. The question of how the market institution calculates the trading price then arises. Studies of other markets, such as the stock exchange, have shown that in an ideal DSA market, the following properties should be satisfied [11]:

A. Individual rationality (IR)

This property defines that no players should lose from joining a DSA so that the trading price is always less than or equal to the bidding price and more significant than the asking price $BP_k \geq TP_k \geq SP_k$.

B. Balanced budget (BB)

There are two types of BB for the mechanism design: strong and weak. In a strong BB, the auctioneer does not gain or lose utility; however, in a weak BB, the auctioneer does not lose utility but might gain it.

C. Truthfulness or incentive compatibility (IC)

Strong notion and weaker notion are two types of IC. The strong notion IC is a dominant strategy where showing the true value to all players is not mandatory. However, in weaker notion IC, players are in Nash equilibrium, and all players show their true values and stay truthful.

D. Economic Efficiency (EE)

This property states that the sum of the utility of all players (i.e., social welfare) should be the best possible outcome.

III. Types of DSA

A. Average Mechanism

Players (consumers and prosumers) in the average mechanism follow natural ordering, and a breakeven index k is calculated, where BP and SP are plotted to calculate the equilibrium price. The market institution selects the first k consumers and first k prosumers to trade energy. The trading price in the average mechanism is the mid-market value i.e. $TP_k = (BP_k + SP_k) * 0.5$. The average mechanism follows individual rationality (IR) due to the ordering, balanced budget (BB) as all utility stays between players, and Economic Efficiency (EE) as the traded energy remains within k players who value them the most. However, it does not follow incentive compatibility (IC) as consumers have an incentive in submitting lower bidding price and prosumers in submitting higher asking price. A multi-round double auction with an average pricing mechanism framework provides various advantages in terms of technical and computational viewpoints [16].

B. Vickrey-Clarke-Groves (VCG) Mechanism

The VCG mechanism focuses on social welfare while attaining truthfulness. In this mechanism, the market institution follows natural ordering to calculate the breakeven index k. Like the average mechanism, the first k consumers are selected to trade energy with the first k prosumers. As per table I, each consumer pays the lowest equilibrium price, and each prosumer receives the highest equilibrium price. The VCG mechanism is IR as consumers pay less than the true value and prosumers receive more than their true value, TF, as consumers and prosumers determine the trading price; and EE because the social welfare is optimised. However, it does not follow BB as the auctioneer/market institution incentivises the trade. Demonstration of overall payments between VCG and optimal mechanisms shows that VCG pays $\sqrt{\boldsymbol{n}}$ times the actual cost where n is the number of players [17]. Another study [18] implemented VCG mechanisms for energy allocation and trading between multiple consumers and a single prosumer equipped with solar PV.

C. Trade Reduction Mechanism

After natural ordering and calculating the breakeven index in the trade reduction mechanism [19], the market institution selects k-1 consumers and k-1 prosumers to trade energy. The first k-1 prosumers trade energy and receive SP_k, and the first k-1 consumers pay BP_k to the auctioneer or market institution. Properties that the trade reduction mechanism follow are IR as consumers pay less than the true value and prosumers receive more than the true value, and TF, as selected consumers and prosumers have no revenue in changing from their original state since it will not affect the trading price. However, this mechanism is considered as having a weak BB as the auctioneer is left with surplus energy, and not EE as the kth consumer and prosumer are not able to trade energy. Also, the kth player will change the price if we try to include it in the market, hence, making it untruthful.

TABLE I. Possible Cases To Calculate Equilibrium Price

	$SP_{k+1} > BP_k$	$SP_{k+1} \leq BP_k$
$BP_{k+1} < SP_k$	[SP_k, BP_k]	[SP_k, SP_{k+1}]
$BP_{k+1} \geq SP_k$	[BP_{k+1}, BP_k]	[BP_{k+1}, SP_{k+1}]

TABLE II. Comparative Analysis Of Various Mechanisms Using DSA

Property Name	Name of the Mechanism			
	Average	*VCG*	*Trade Reduction*	*McAfee*
Individual Rationality	Yes	Yes	Yes	Yes
Balanced Budget	Yes	No	No	No
Truthfulness	No	Yes	Yes	Yes
Economic Efficiency	Yes	Yes	No	No

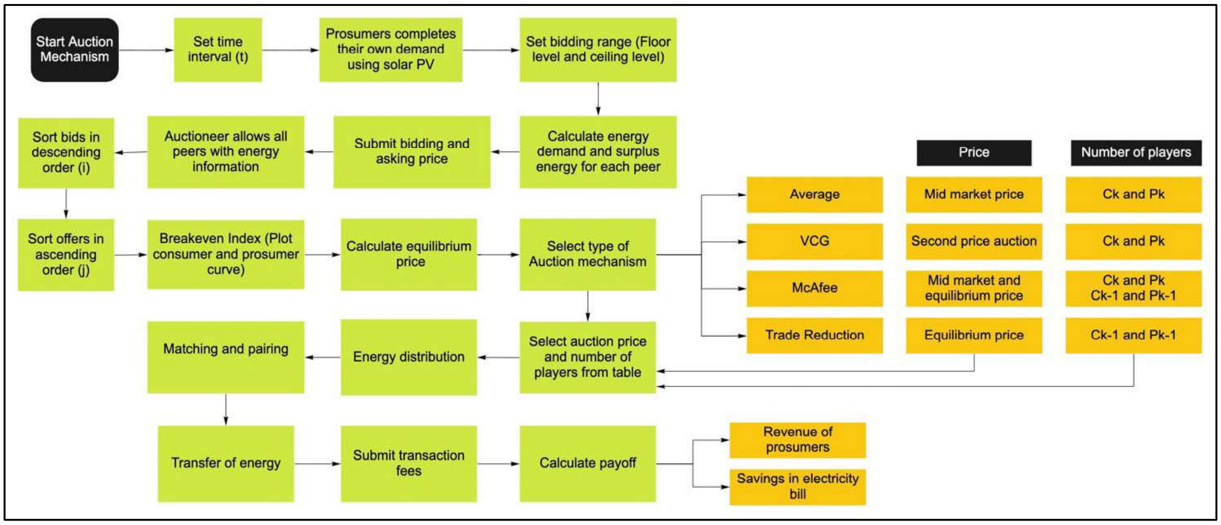

Figure 1. Flowchart of the trading algorithm

D. McAfee Mechanism

The McAfee mechanism [20] is a variation of the Trade Reduction mechanism. After going through the natural ordering and calculating the breakeven index, it checks the trading price. If $BP_k \geq TP_k \geq SP_k$, then the first k consumers and first k prosumers trade energy. Otherwise, the first k-1 prosumers trade energy with the first k-1 consumers, just like the trade reduction mechanism. Therefore, this mechanism is also IR and TR. However, in the second case of k-1 players, this mechanism does not follow BB and EE. In a comparison study of the McAfee based double auction algorithm and centralised algorithm for P2P energy trading within neighbourhoods, the flocking based McAfee mechanism shows better results in energy trading [21]. The McAfee mechanism is used in [12], for distributed double auctions to determine the auction winners.

IV. System Model

Consider a distribution network with microgrids; each microgrid consists of multiple peers that can either be a prosumer with a solar photovoltaic generation or a consumer with no generation. Let us denote the total number of consumers in a microgrid N_i as i_C and the total number of prosumers as i_P where $i_T = i_C + i_P$. Each consumer is indexed as C where $C \in \{1,2, \ldots . i_C\}$ and each prosumer is indexed as P where $P \in \{1,2, \ldots . i_P\}$. Both the consumers and prosumers have continuous two-way communication of energy data and power flow between them. At a time interval T, a prosumer i_P meets its energy demand from solar PV and, if there is any surplus after completing its own demand, it can sell the surplus energy to other consumers in the microgrid. Similarly, if the prosumer's surplus energy is zero, a prosumer can act as a consumer and buy from other prosumers at another time interval. Therefore, we can assume that this microgrid is working on island mode most of the day-time and asks for energy from the grid during night time.

As the interests of the peers conflict with each other (prosumers wants to sell surplus energy at a high price while the consumers want to buy deficit energy at a low price) and the players are selfish, an auctioneer is required to coordinate trading between peers. Each microgrid in the network is connected to the auctioneer, which acts as a network's central controller. The auctioneer ensures that the energy generated from renewable sources and the energy demand of the MGs are balanced within the network. By optimally trading energy using game theory, reducing network losses and optimising energy cost, the common goal of all players is achieved. The auctioneer, therefore, coordinates the energy trading among MGs so that this common aim is achieved. The objective of the auctioneer is to maximise the system efficiency and social welfare of the network. Effective market equilibrium is also attained when the auctioneer maximises social welfare. Higher social welfare leads to increased revenue of prosumers and savings in electricity bills. Social welfare can be mathematically expressed as:

$$SW = max\{\sum_{C=1}^{i_C} U(Qty_{Cons}) - \sum_{P=1}^{i_P} U(Qty_{Pros})\} \quad (1)$$

The utility of the consumer i_C can be expressed as the $U(Qty_{Cons})$ and the utility of the prosumer i_p can be expressed as the $U(Qty_{Pros})$. Flowchart of the trading algorithm for P2P energy trading based on various double auction mechanisms is shown in Fig. 1.

Time interval t_i is set for double auction that can be 5 minutes or 1 hour depending on the load requirement. In the proposed trading algorithm, t_i is set as 5 minutes. There are no restrictions assumed on the maximum energy that each prosumer can sell and each consumer can buy. The objective of the trading algorithm is to complete the energy demand of the microgrids with the surplus energy generated by the prosumers. Peers in the network submit their bidding and asking price to the auctioneer. It should be noted that no peer can expect to improve their utility by deviating from the true price. True price falls under floor and ceiling price set by the auctioneer, and both consumers and prosumers operate within limits. BP_n be the set of bidding prices of all consumers submitted to the auctioneer between t_i and t_{i+1} and Qty^n_{Cons} be the energy demand of all consumers. SP_n be the set of selling prices of all prosumers submitted to the auctioneer between t_i and t_{i+1} and Qty^n_{Pros} be surplus energy of all prosumers. At t_i, all peers send information like energy demand, energy generated, bid price and sell price to the auctioneer. The auctioneer allows all peers to view the bid price and sell offers before matching and pairing. Rather than sending auction request to a single consumer, auctioneer send multiple auction request simultaneously, each of which has a predefined number of iterations. In the next step, the algorithm sorts the selling prices in increasing order $SP_1 \leq SP_2 \leq \cdots \leq SP_n$. This increasing list of selling prices is used as the prosumer curve to calculate the breakeven index. Similarly, the algorithm sorts the bidding prices in decreasing order $BP_1 \leq BP_2 \leq \cdots \leq BP_n$. This decreasing list of bidding price is used as consumer curve to calculate breakeven index. According to the sorted list, the algorithm plots the prosumer and consumer curve and calculates the intersection point of these two curves. The intersection point of the consumer and prosumer curve is the equilibrium price $\mathrm{p_e}$. The trading algorithm now selects the best DSA mechanism. According to the DSA mechanism selected by the algorithm, auction price p_{auc} is calculated. There might be a chance that the equilibrium price is equal or not equal to auction price. $\mathrm{p_e} = \mathrm{p}_{auc}$ or $\mathrm{p_e} \neq \mathrm{p}_{auc}$. Number of consumers (C_k / C_{k-1}) and prosumers (P_k / P_{k-1}) are determined that can participate in trading at t_i with reference to the selected DSA mechanism. In next step, allocation of energy is calculated. Each prosumer can sell its surplus energy to consumers when the energy demand is equal to the surplus energy. If the surplus energy is higher, a prosumer will make multiple pairs with consumers and similarly if the energy demand is higher, a consumer will make multiple pairs. Energy distribution is this algorithm works according to the sorting list. Equal distribution and proportional distribution of energy are two techniques commonly used for distributing surplus energy within consumers. First bid and offer from the sorted list are selected from the sorted list and paired to check for a match. This methodology of auction keeps on working till the network has found an equilibrium point or the game reaches its maximum number of rounds. As we proceed with the maximum number of rounds in the game, buying price and selling price keeps on changing for the next round. The peers submits a transaction fee to the grid for using the infrastructure which is 2% of the revenue generated by the peers.

The mechanism accumulates all the consumers from unconfirmed transactions that are unable to meet their energy requirement due to the intermittent nature of renewable resources and varying demand of the users. We consider that this group of consumers will ask the main grid to complete their demand and form a new coalition. In any case, equilibrium was not found at the end of the game, consumers buy the energy required from the main grid at the tariff price which is always higher than the price offered during auction. Similarly, if a prosumer cannot sell the surplus energy, it is sold to the main grid at feed in tariff which is always lower than the auction price.

In order to account for the geographical distance of the consumers and prosumers, the model considers the microgrids in a ring network. More specifically, distribution losses are reduced due to the ring network of microgrids as the distance between two peers gets reduced. Furthermore, ring networks are considered to have less power losses when compared with radial networks. The proposed trading algorithm does not consider network constraints related to voltage and power during trading. The study tries to focus on the comparative analysis of various auctions.

V. SIMULATIONS

This section demonstrates comparative analysis results from simulations to exhibit how different DSA mechanisms work for P2P energy trading. A P2P matching algorithm is developed in this study in MATLAB 2021 using auction mechanisms to enable trading between multiple microgrids. We considered IEEE low distribution LV feeder data [22] for multiple microgrids for simulations. We considered a residential network of 5 microgrids with an equal ratio of consumers and prosumers. This residential network also consists of electric vehicle (EV) charging points equally spread in the five microgrids. Multiple microgrids are assumed as distinct parts of the trading algorithm. Each microgrid has ten consumers, ten prosumers and 3 EV charging points. The trading period set for all trading algorithms is 5 minutes, and players are allowed multi-shot bidding. Daily demand and solar PV generation profiles with 5-minute intervals are shown in Figures 2 and 3.

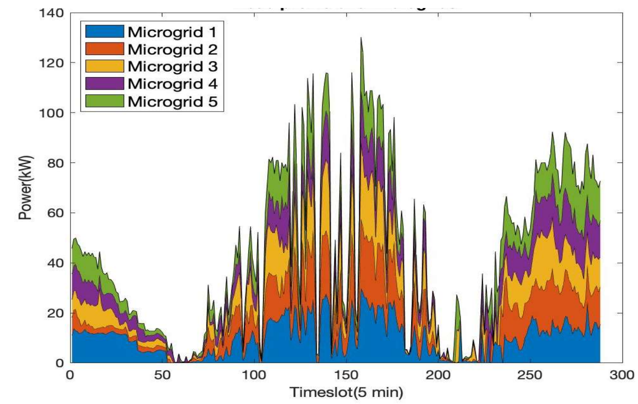

Figure 2. Load profile of 5 microgrids, each consisting of 10 consumers and 3 EV charging points

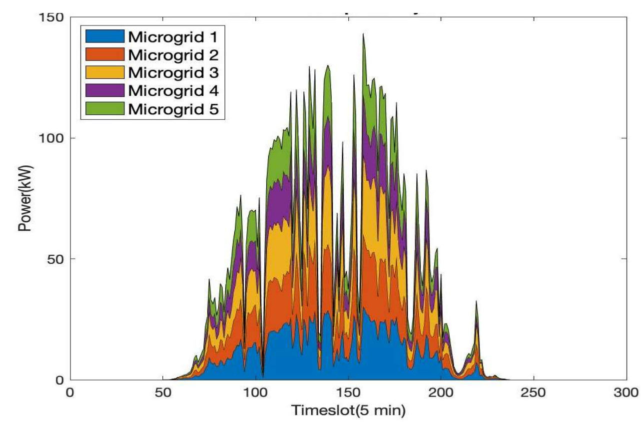

Figure 3. Energy generated of 5 microgrids from solar PV

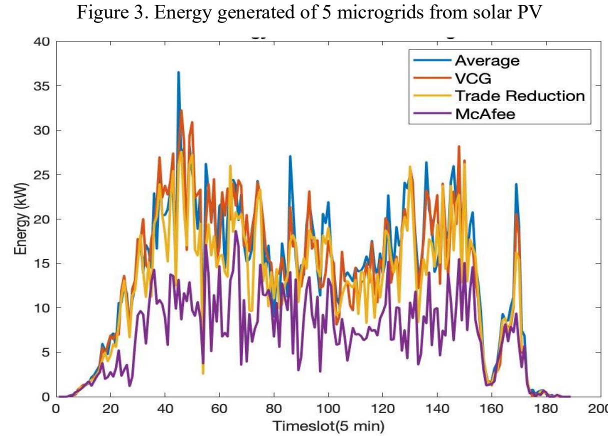

Figure 4. Total energy traded by different mechanisms using DSA

Microgrid demand shown in figure 2 is the sum of the energy demand of consumers and prosumers after trying to fulfil their own demand using solar PV. There are sudden load drops at specific time slots due to the intermittent nature of solar PV. To trade energy at each time interval T, the bidding range is selected from €0.09/kWh to €0.20/kWh; i.e. the floor level is €0.09/kWh and the ceiling level is €0.20/kWh. We can divide the 24-hour load profile shown in figure 2 and energy generation shown in figure 3 into peak hours and non-peak hours. According to the results, peak hours lie from 0800 Hrs to 1500 Hrs (Timeslot 97 to 180) and non-peak hours from 1500 Hrs to 0800 Hrs (Timeslot 180 to 288 and timeslot 1 to 96).

Figure 4 presents the results of the DSA with different mechanisms for 24 hours divided into 5 minutes intervals. The equilibrium price is calculated for all types of double auctions using natural ordering and the breakeven index (k). Players falling outside the breakeven index are allowed to bid again until the demand of the consumers is fulfilled.

The total energy traded by average, VCG, Trade Reduction, and McAfee are 2551 kWh, 2575 kWh, 2262 kWh, and 1229 kWh, respectively. To compare different mechanisms, we evaluated the sum of energy savings of consumers and revenue generated by prosumers. These values can be combined to determine the social welfare of individual microgrids, as illustrated in figure 5. The different mechanisms result in different levels of social welfare. These differences can be explained by the change in trading price at each time interval and the different methodologies for calculating the trading price for each mechanism. When the different mechanisms are simulated for the same surplus energy data, bidding price, and energy demand data, the results explain the best suitable mechanism for P2P energy trading. A detailed evaluation of results indicates that the average mechanism is the most appropriate mechanism in terms of social welfare. The average mechanism provides consumers and prosumers better energy savings and revenue generation than any other mechanism in the literature.

Figure 6 represents the transactions v/s shots for 288-time intervals. Consumers and prosumers get multiple shots to trade until unless energy demand or surplus energy of the microgrid becomes zero. A shot can have multiple transactions, and the relation between them is shown in figure 5. Average and VCG mechanisms have almost same trend as shown in the figure; however, trade reduction and McAfee mechanisms have fewer shots v/s transactions. This is due to the fact that trade reduction and McAfee mechanisms trade less energy as compared in figure 4.

Table III shows the energy traded, social welfare, and net savings of consumers of multiple microgrids for various mechanisms. The results of time of usage (ToU) indicates that the DSA mechanisms assume ToU tariff for bidding and hence, have a shorter bidding range. In this ToU scenario, peak hours bidding range is €0.16/kWh to €0.20/kWh, and non-peak hours bidding range is €0.09/kWh to €0.15/kWh. It is evident from the table that in the typical scenario where the bidding range is wide, less energy is traded. However, a higher benefit is provided in terms of social welfare. However, when using a ToU tariff, the amount of energy traded is high but social welfare is low. Hence, we can say that a more comprehensive bidding range will lead to more social welfare in double auction mechanisms.

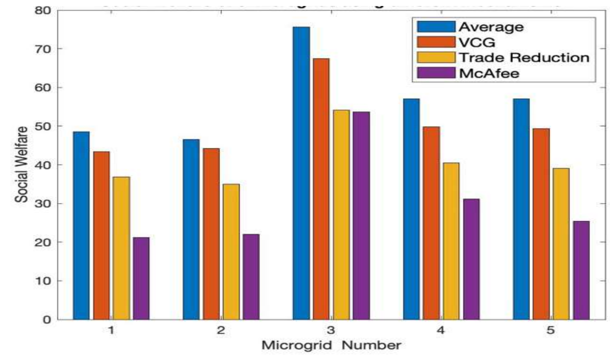

Figure 5. Social welfare of different mechanisms in multiple microgrids

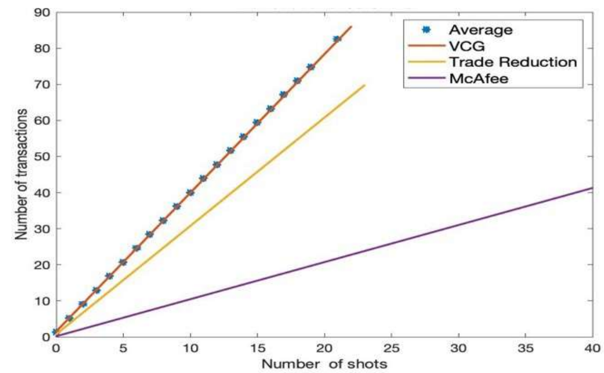

Figure 6. Transactions v/s shots for different DSA mechanisms

TABLE III. ENERGY TRADED, SOCIAL WELFARE AND NET SAVINGS OF CONSUMER FOR FIXED BIDDING RANGE AND TOU BIDDING RANGE

	Name of the Mechanism			
	Average	*VCG*	*Trade Reduction*	*McAfee*
Energy Traded (kW)	2551	2575	2262	1229
Energy Traded (kW) - ToU	**2638**	**2605**	**2363**	**1314**
Energy traded (%)	49%	49%	43%	23%
Energy traded (%) - ToU	**50%**	**50%**	**45%**	**25%**
Social Welfare ($)	281	262	207	119
Social Welfare ($) - ToU	**106**	**97**	**81**	**53**
Net savings of consumer ($)	156	153	115	48
Net savings of consumer ($) -ToU	**61**	**58**	**46**	**41**

VI. CONCLUSION

This work explains four double auction mechanisms for P2P energy trading in terms of their economic properties and demonstrates how to implement them in a low voltage distribution network. To evaluate the performance of the mechanisms, a comparison of energy trading and social welfare is simulated. According to the results, it can be concluded that energy trading and social welfare is highly achievable using an average mechanism. Compared with other mechanisms, the average mechanism provides fewer transactions and less complexity, making it easy to implement. Based on the proposed comparative analysis, we conduct simulations on the bidding range available to the consumers and prosumers, which shows that social welfare is highly achievable when using a high bidding range. For real time implementation, the proposed trading algorithm can be used on low voltage feeder to select the best possible mechanism for each time interval. This algorithm can extract data from smart meters and generate revenue for each peer in the network.

For future work, we seek to consider trading from a microgrid to another and their implications in real-life applications. We plan to use real time datasets with different ratios of DER's to explain the patterns of these four mechanisms in large scale P2P energy trading projects.

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